Home Appliance Control System based on Robust Indoor User Localization using Wifi Signals

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Abstract—An application is introduced to control home appliances on the basis of an indoor user localization system using Wifi signals. In this application, the user heads his smart device (smartphone or tablet) to the appliance needed to control like bulb, television, air conditioner, fan, security camera... just similarly to using a remote control. On the basis of the user location provided by a localization system, the heading orientation and the tilt angle of his smart device, the system will detect the target appliance by regarding a predefined map, and show the corresponding control panel on the smart device's display, allowing the user to apply control command to the appliance. A small program installed on the smart device regularly scans the signal strengths to surrounding Wifi access points to enable calculating the user location in 3D space by a robust hybrid method, which is based on both geometrical and probabilistic approaches. A central server is set up to realize the control commands received from the smart device.

Keywords—Home appliance control; Wifi-based localization; indoor user localization; ubiquitous computing; distributed intelligence

I. INTRODUCTION

The proliferation of smart hand-held devices (smartphones and tablets) with their powerful computing strength has created a new class of applications which relies on the mobility. In this paper, a robust Wifi-based localization technique is introduced as the basis of a home appliance control application. This application is a ubiquitous computing extension to existing classical smart-home systems with electrical equipment controllable via a central server, and is designed to address the fact that every appliance requires specific remote control which is not always with the user when he needs.

Location information is an important tool for enabling multiple applications, e.g., community settlement planning, traveling, mining, surveillance, monitoring, military applications, and nowadays the development of location-based services (LBS) and engineering. Localization techniques have been actively studied recently due to service as well as safety and security matters. There are many localization systems with different architectures, configurations, accuracies and reliabilities. GPS (Global Positioning System) is the most popular system to find the location of objects, in which a worldwide satellite network is used. A triangulation process is applied to the received signals from multiple satellites to determine the location with claimed accuracy of up to 3m [1]. However, GPS is generally an outdoor localization system as the signals are heavily attenuated and reflected by building materials, making the positioning accuracy dramatically degrades or even unavailable. This drawback has boosted the search for indoor localization schemes with many techniques and approaches proposed.

Previous research and development for indoor localization includes cellular networks, infrared, ultrasonic, computer vision, RFID... [2,3]. However, these technologies suffer either from the limited accuracy, range, lacking of the infrastructure, or high deployment price. Due to the widespread availability of local wireless networks, the interest in localization based on Wifi signal strengths are increasing because no additional infrastructural costs beyond the existing Wifi infrastructure is required, making it become a promising

indoor localization scheme. Much research has been devoted to methods for the wireless localization, but can be categorized into two main approaches: geometrical-calculation based and finger-printing based (or scene-analysis based) [1].

The former approach relies on measurement of geometrical parameters (e.g., distance, angle) from the object of interest to the neighbor base stations. These parameters allow estimating the object position via calculations. The most popular methods of this approach includes angulation based on AOA (angle of arrival) [4,5], lateration based on TOA (time of arrival), RTOF (round-trip time of flight) or RSSI (received signal strength index), and hyperbolic lateration based on TDOA (time difference of arrival) [2,6]. For Wifi networks, since AOA, TOA, RTOF and TDOA are all not measurable by conventional receivers, hence unavailable in general, RSSI is the parameter used in most of studies following this approach with the help of a radio-frequency (RF) propagation model.

The latter consists of collecting a reference database of RSSI at strategic points in the environment for later matching. A number of matching techniques have been developed such as probabilistic methods [7], K-nearest neighbor (KNN) [8], artificial neural networks (ANN) [9,10], support vector regression (SVR) [11,12],... among which probabilistic methods are the most advanced as the uncertainty of RSSI is taken into account.

Geometrical approach gains over the other by a lower pre-deployment cost for site survey, but instead, an environment map is required in principle so that RSSI attenuation through walls and floors can be taken into account in calculations. For finger-printing methods, the RSSI map in addition to being established at pre-deployment phase must be adjusted to adapt any change of environment. However, in return, as the radio propagation characteristics for Wifi in unstructured environments are complicated, the accuracy of geometrical methods is lower, with the claimed accuracy of 5m [1] in comparison with 3m for finger-printing methods [8].

In this paper, a hybrid approach is introduced to address the Wifi-based localization in 3D space. Like geometrical approach, by measuring RSSI, distances to the neighbor access points (APs) are estimated. However, probabilistic characteristics are included to take advantage of the RSSI uncertainty. An optimization process is also applied to tune system parameters for best fitting with the devices in use.

The remainder of this paper is organized as follows. In Section II, the general architecture of the appliance control system is introduced. After that the localization method is explained in Section III. Experiment results are then presented and discussed in Section IV, and finally, concluding remarks are given in Section V.

II. SYSTEM ARCHITECHTURE

Figure 1 shows the general schematic illustration of the proposed system for an example house of a number of rooms and corridors which can be commonly referred as zones. The zones can be disposed in multiple floors. Electrical appliances, including bulbs, lamps, fans, air conditions, televisions, security cameras..., in the house are connected to a central server so that they can be controlled and their states can be managed from this server.

The remote control app installed on the user's smart device (smartphone or tablet) has two modes: manual and automatic. In manual mode, the user can choose to navigate to the control panel corresponding to the appliance of interest, then presses the function buttons. In automatic mode, the user only needs to head the smart device toward the appliance of interest, and the corresponding control panel will be shown automatically. The system determines the desired appliance on the basis of the locations of the user and the appliance, and the tilt angle of the smart device. In automatic mode, the system only allow the user to control the appliance associated to the zone that he stays in, while in manual mode, the user can navigate to the control panel of any appliance in the system regardless where he is on the Internet.

The server stores an environment map (in XML format) which includes information about floors, zone boundaries, walls, location of each appliance, and appliance-zone association mapping. The association

mapping is used by the system to know which appliances can be controlled from each zone in automatic mode. For most of appliances, each one is associated only to the zone that includes it. However, in generic cases, an appliance can be associated to more than one zone. For instance, for the security camera in Figure 1, it would be more convenient to be able control the camera from any zone in the house.

The localization system relies on a number of Wifi APs disposed in the environment. The user location is determined by his smart device. As the user moves in the environment, the app installed on his smart device regularly scans the Wifi signals from neighbor APs and send the collected RSSI to the central server through the WLAN. Based on the RSSI information, the server will estimate the user location by using the proposed method that will be described in Section III. The localization result consists of a 3D position with (x, y, z) coordinates, together with the floor and the zone that the user belongs to. Once the user press a button on the control panel shown on the smart device, the app sends a corresponding command to the server. All appliances and control tasks are managed and implemented on this server.

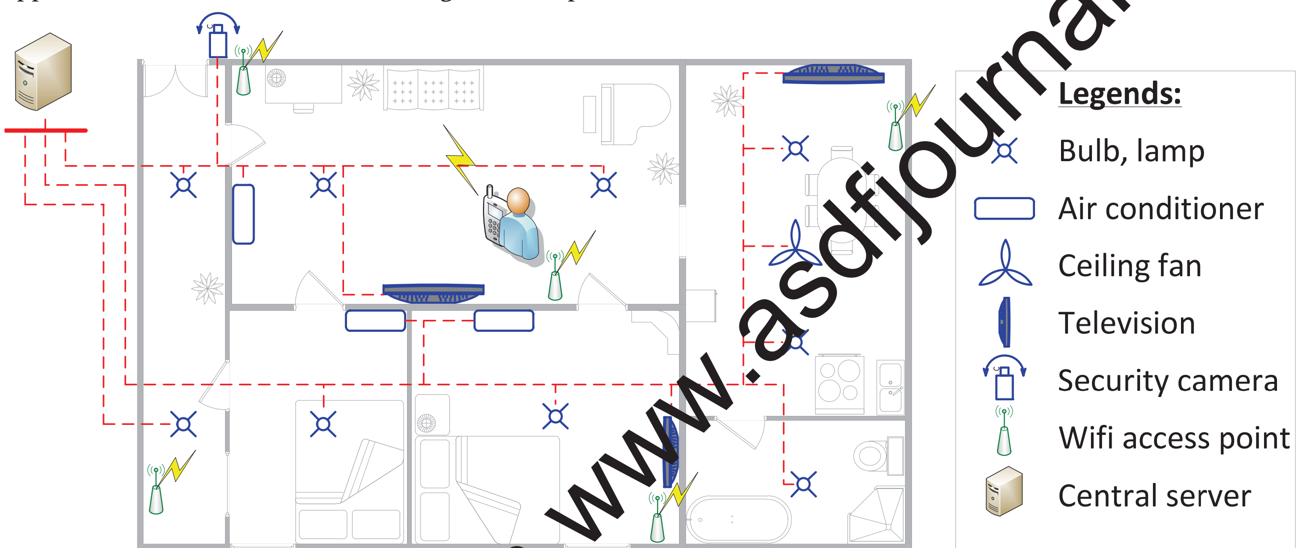

Figure 1. General system architecture

III. ROBUST WIFI-BASED USER LOCALIZATION

In this section, a hybrid approach is introduced for user localization using Wifi RSSI. From a tuple of RSSI information received from the user's smart device, the system needs to determine the user location.

A. Probabilistic Propagation Model

With conventional Wifi receivers, distance to APs can only be estimated from the measured RSSI with help of a RF propagation model which is constructed based on the fact that a radio wave traveling through a certain environment will undergo specific types of signal attenuation. To start off, the empirical model widely used in previous works [6,8,13] is considered:

$$P = P_0 - 10n\log\left(\frac{r}{r_0}\right), \qquad (1)$$

where P_0 is the known signal power at a reference distance r_0 in dBm, P is the signal power at an unknown distance r, and n is the path-loss exponent indicating the rate at which the path loss increases with distance. Equation (1) expresses the relation between the RSSI P and the distance r between receiver and

AP, where parameters P_0, r_0 and n can be determined from experiments. Once the parameters are determined, the distance can be estimated given the RSSI.

Equation (1) is a propagation model in an environment without obstacle between the AP and the receiver. When walls and floors are considered in calculation, attenuation due to these factors must be included, and the propagation equation becomes

$$P = P_0 - 10n\log\left(\frac{r}{r_0}\right) - k_d \sum_{i=1}^{n_w} \frac{d_i}{\cos\beta_i}, \qquad (2)$$

where n_w is the number of walls and floors in the middle of the AP and the receiver, d_i is the thickness of the i^{th} wall/floor, β_i is the angle of arrival corresponding to the i^{th} wall/floor, and k_d is the attenuation factor per wall/floor thickness unit, as illustrated in Figure 2. In general cases, k_d can be extended to be dependent specifically on each wall/floor.

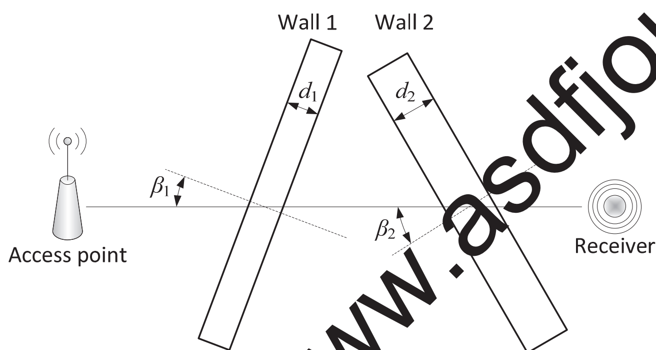

Figure 2. Wifi signal attenuation through walls/floors

Equation (2) is a deterministic model, i.e. the uncertainty of RSSI at a distance is not taken into account. To address this limitation, a probabilistic model is used. In reality, given the RSSI P, the distance r might not be exactly the value calculated from Eq. (2), but is within a range around this value, which is denoted by $\bar{r}$. To be more precise, $\bar{r}$ will be the nominate value of the distance r with highest probability. Given a RSSI P, the distribution of the distance is assumed to follow the normal (or Gaussian) distribution with median $\bar{r}$:

$$\rho(r,P) = \Pr(r|P) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r-\bar{r})^2}{2\sigma^2}}, \qquad (3)$$

where σ is the standard deviation, which is also a function of P. For simplicity, σ is assumed to be related to $\bar{r}$ by a linear relation:

$$\sigma = k_\sigma \bar{r}, \qquad (4)$$

where k_σ is a constant, which also needs to be determined from experiment data.

B. User Localization

With the probabilistic propagation model, the user localization method can be established. The main idea is to find the location with maximal summation of probabilities corresponding to the visible APs, i.e., maximizing

$$\rho_{\Sigma}(x,y,z) = \sum_{i=1}^{n_{AP}} \rho\left(r_i(x,y,z), P_i\right), \qquad (5)$$

where n_{AP} is the number of visible APs, $\rho_{\Sigma}(x,y,z)$ is the probability that the user is located at position (x,y,z), and $\rho\left(r_i(x,y,z),P_i\right)$ is the probability component based on the i^{th} visible AP.

The search process can be achieved by gridifying the space surrounding the environment into a number of points and calculate ρ_{Σ} for each of them to find the point that maximizes ρ_{Σ}, which will be the estimated user position. The wall and floor information involved in these calculations is extracted (using XQuery) from the environment map mentioned in Section II. With a large environment where the number of points is big, it is possible to reduce the searching time by first gridifying the space with fewer points to find a rough position, then repeating the same process once or twice with the subspace around this position for fine tuning.

Once the user position with (x,y,z) coordinates is available, it is possible to determine the floor and zone that he belongs to by regarding the environment map. With all this location information, together with the heading and tilt angles of the smart device, the system is able to find out the appliance of interest that the user intends to control.

C. Parameter Estimation

For the localization system, there are totally five parameters to be determined: P_0, r_0, n, k_d and k_{σ}. Except k_{σ}, the other parameters can be estimated separately from individual measurements in a straightforward manner. However, the values of these parameters can be slightly affected by the assumptions taken in the RF propagation model. For this reason, genetic algorithms (GAs) are used to find the optimal parameter set, all together.

Genetic algorithms [14] are global search techniques modeled after the natural genetic mechanism to find approximate or exact solutions to optimization and search problems. In a GA, each parameter to be optimized is represented by a gene; moreover, each individual is characterized by a chromosome, which is actually the above set of parameters awaiting optimization. To assess the quality of an individual, a fitness function (objective function, or cost function) must be defined. For the localization module, the fitness function Φ is defined as the root mean square of the localization error

$$\Phi = \left(\frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2 + (\hat{z}_i - z_i)^2 \right)^{1/2}, \qquad (6)$$

where N is the number of measurements, $(\hat{x}_i, \hat{y}_i, \hat{z}_i)$ and (x,y,z) are the real and the estimated user position, respectively.

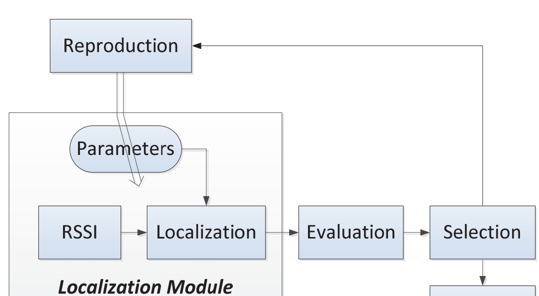

Figure 3. Optimization of system parameters using GAs

In brief, a GA starts by generating an initial population (or initial generation); then, the quality of each individual is evaluated by using the fitness function. After one generation, only the advantageous individuals survive and reproduce to generate a new population. By this process of selection from generation to generation, the quality of the offspring is improved in comparison with their ancestors, as shown in Figure 3. During the creation of a new generation, a portion of the surviving individuals is recombined randomly via the so-called crossover and mutation operations, being adopted from natural evolution.

At the initial phase, the population consists of randomly generated heterogeneous chromosomes. After that, all chromosomes go through three principal parts: evaluation, selection and reproduction modules. The population will be improved as fitter offspring individuals replace parents. The procedure is repeated until either a maximum number of generations is reached or an optimal solution is obtained, whichever is earlier. In this study, the searching procedure is repeated until a parameter set satisfying the optimization criteria with acceptable tolerance is found.

The advantages of GAs over other searching algorithms are that they do not require any gradient information neither continuity assumption in searching for the best parameters, and that they can explore many characteristics at once, which is necessary when dealing with complex problems.

IV. Experiment Results

For experiments, the devices and appliances are disposed in three floors (8^{th}, 9^{th} and 10^{th}) of an eleven-floor building, as shown in Figure 4. In 23 zones of the 8^{th} floor with total area of $1656m^2$, 6 APs are disposed. For the 9^{th} floor, there are 22 zones ($1512m^2$) and 4 APs; and for the 10^{th} floor, there are 19 zones ($1368m^2$) and 5 APs. All floors are of 4m height with 0.2m-thick concrete walls and floors. All APs are of Linksys™ WRT120N model which is compliant with 802.11 b/g/n standards, and are fixed just under the ceilings.

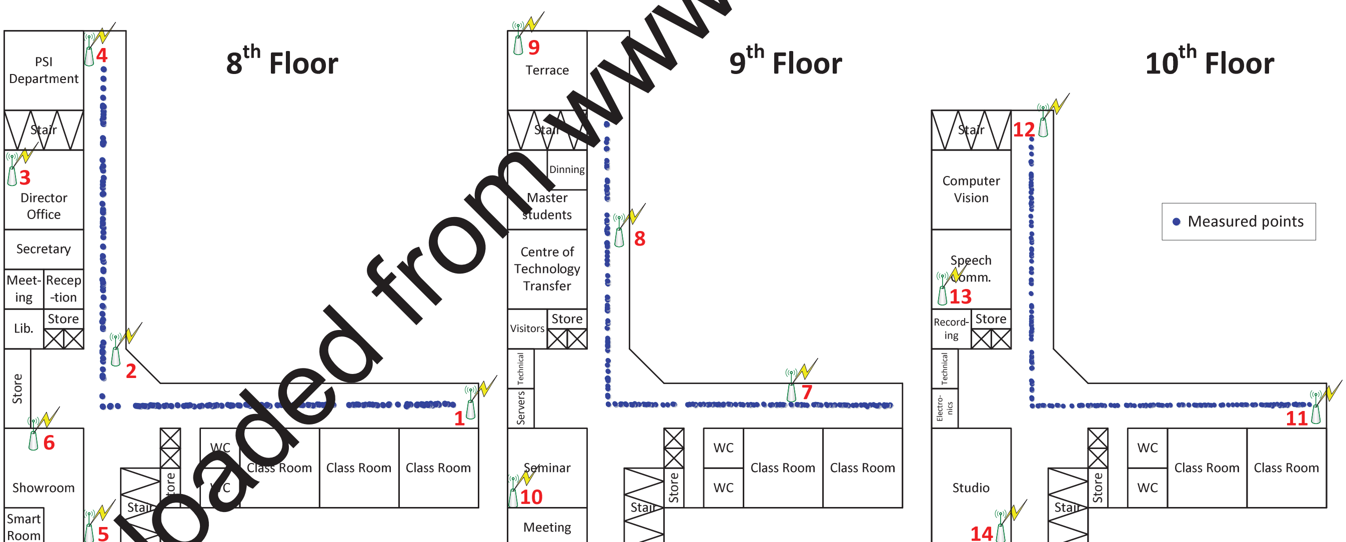

Figure 4. Ground plan of three floors in experiments, with Wifi AP disposal, and collected training data

Two smart devices are used in this study. The first one, which is a smartphone of HTC™ Desire S™ model running Android™ 4.0, is used to collect training data; and the second one, which is a smartphone of Samsung™ Galaxy Nexus™ model running Android 4.1.2, is used in the test of localization performance, and in the control of appliances. However, in principle, any smartphone or tablet running Android can be used. The Wifi scanning rate of the Android app is set to once every 2 seconds.

First, data are collected to tune system parameters, as discussed in Section III.C. A person holding the first smartphone moves slowly at a constant speed along the corridors on the three floors to measure the Wifi signal strengths. There are totally 672 measurements carried out for the training data. For each

measurement, the RSSI of visible APs are saved. The training process using GAs is set up with configuration provided in Table I. With these data produces the optimal parameter values given in Table II, with the root mean square error of 1.63m.

TABLE I. Genetic Algorithm Configuration

Parameter	Value	Parameter	Value
Population size	20	Tolerance	10^{-6}
Elite count	5	Selection	Uniform
Crossover fraction	0.5	Crossover	Scattered
Time limit	No	Mutation	Uniform
Maximal generations	No	Creation population	Uniform

TABLE II. Optimized System Parameters

Parameter	Value	Parameter	Value
P_0	-41 dBm	r_0	5 m
n	1.1	k_d	49.2[illegible] dBm m^{-1}
k_σ	1.0035 m^{-1}		

With the optimized parameters, the propagation model in Eq. (1) is compared with measurements of RSSI to APs with no wall/floor in the middle of the lines of sight (LOS), as depicted in Figure 5. With a fixed AP, the smartphone is placed at distances from 5 to 100m, with increment of 5m. At each distance, 5 measurements are carried out, and then the average value is used and shown in this figure. It can be observed that the tuned model is closed to the experiment data, with highest error of 1.9dBm. This comparison verifies the deterministic propagation model of Wifi signals.

Figure 6 shows the probabilistic propagation model with the tuned parameters. For each RSSI value, a probability distribution function (PDF) is established following the normal distribution with median value calculated with help of the deterministic model.

On the basis of the probabilistic propagation model, localization experiment is carried out to verify the performance. A person holding the second smartphone moves around the 8th floor to collect RSSI information. The measured points are depicted in Figure 7 by solid dots. With these data, including 191 points, the localization method described in Section III is applied, and the results are shown in the same figure by circles. The position calculation is done individually for each measurement, without any tracking algorithm or smoothing filter. It can be observed that the localization results are closed to the measured points. The accuracy is 2.27m at precision rate of 90%. The maximal localization error is of 3.18m.

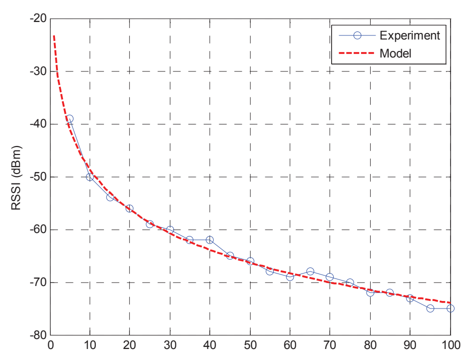

Figure 5. Deterministic propagation model compared to measurements

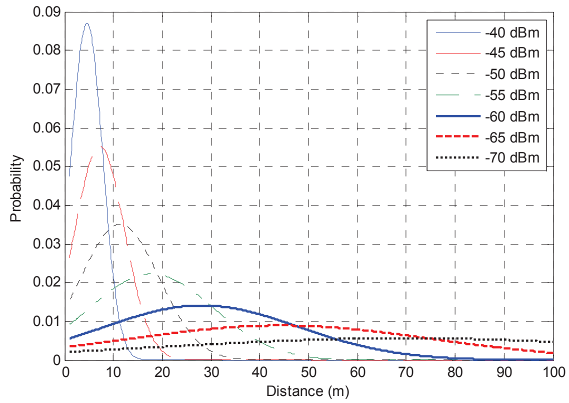

Figure 6. Probabilistic propagation model

Another experiment is carried out for the control of the appliances. The heading and tilt angle tolerances in finding the appliance of interest are set to 15°. The appliances in experiment including a television, a projector, three air conditioners, three bulbs, and a security camera are disposed in the Showroom (9m×13.5m) and the Smart-room (4.5m×4.5m) areas in the 8th floor, as illustrated in Figure 8. Figure 9 shows the remote control panels for air conditioner (with four functions: turn on/off, increase/decrease temperature), bulb (with four functions: turn on/off, increase/decrease brightness) and television (six functions: turn on/off, jump to next/previous channel, increase/decrease volume). The user stands at 8 different locations in the Showroom and Smart-room areas marked in Figure 8 and attempts to control the appliances in the same room, except the camera which can be controlled in both rooms. All control attempts are successful without error.

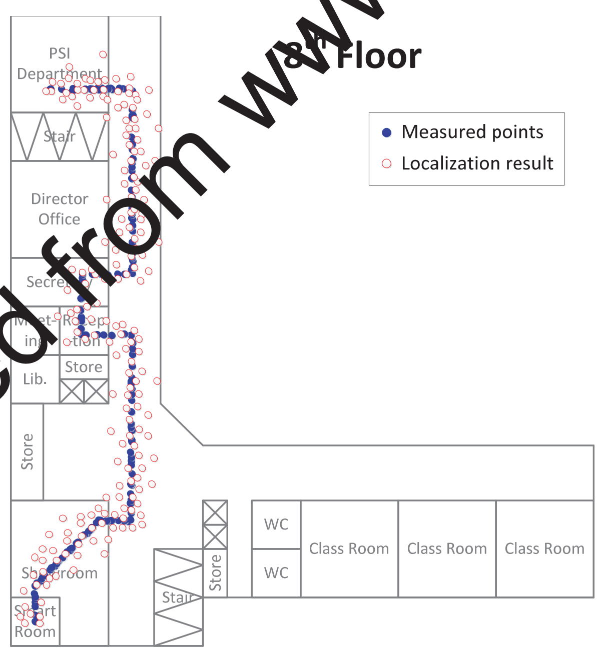

Figure 7. Localization experiment results

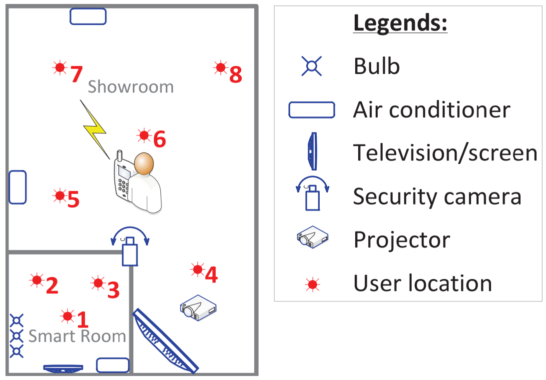

Figure 8. Disposition of appliances in experiment and user locations

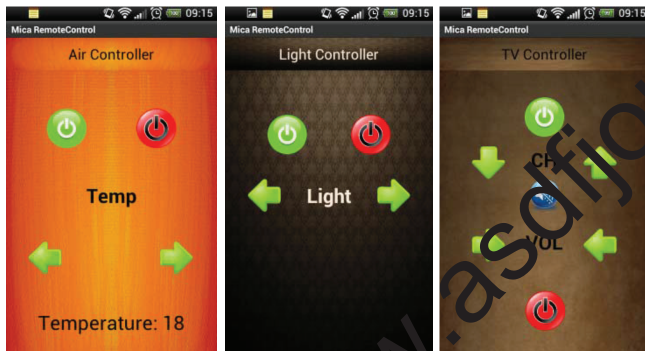

Figure 9. Remote control panels for air conditioner, bulb, and TV

V. CONCLUSION

In this paper, a hybrid robust localization method is introduced which is based on a probabilistic propagation model of Wifi signals. System parameters are tuned by using genetic algorithms with collected training data. Experiment results using Android smartphones show that significantly high accuracy of user localization is achieved. On the basis of the localization system, an application is developed to facilitate the remote control of domestic appliances. In this study, neither tracking algorithm nor smoothing method has been adopted for filtering localization results. This is an open perspective to increase the accuracy of the localization method.

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REFERENCES

[1] D. Munoz, F.B. Lara, C. Vargas and R. Enriquez-Caldera, Position Location Techniques *and Applications*. Academic Press, 2009, ISBN: 978-0123743534.

[2] K. Hakan and H.Y. Shuang, "A survey of indoor positioning and object locating systems," *International* Journal of Computer Science and Network Security, vol. 10, no. 5, May 2010.

[3] H. Liu, H. Darabi, P. Banerjee and J. Liu, "Survey of wireless indoor positioning techniques and systems," IEEE Transactions on Systems, Man, and Cybernetics, *Part C: Applications and Reviews*, vol. 37, no. 6, Nov. 2007, pp. 1067-1080.

[4] S. Sakagami, S. Aoyama, K. Kuboi, S. Shirota and A. Akeyama, "Vehicle position estimates by multibeam antennas in multipath environments," IEEE Transactions on Vehicular Technology, vol.41, no.1, 1992, pp. 63-68.

[5] L. Lazos and R. Poovendran, "SeRLoc: Secure range-independent localization for wireless sensor networks," Proceedings of the ACM Workshop on Wireless Security (WiSe), 2004, pp. 21-30.

[6] J. Figueiras and S. Frattasi, Mobile Positioning and Tracking: From Conventional to Cooperative Techniques, John Wiley & Sons, 2010, ISBN: 978-0470694510.

[7] T. Roos, P. Myllymäki, H. Tirri, P. Misikangas and J. Sievänen, "A probabilistic approach to WLAN user location estimation," International Journal of Wireless Information Networks, vol. 9, no. 3, Jul. 2002, pp. 155-164.

[8] P. Bahl and V.N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," IEEE Conference on Computer and Communications Societies, vol. 2, Mar. 2000, pp. 775-784.

[9] U. Ahmad, A.V. Gavrilov, S. Lee and Y.K. Lee, "A modular classification model for received signal strength based location systems," Neurocomputing, vol. 71, 2008, pp. 2657-2669.

[10] C.-Y. Tsai, S.-Y. Chou, S.-W. Lin and W.-H. Wang, "Location determination of mobile devices for an indoor WLAN application using a neural network," Knowledge and Information Systems, vol. 20, no. 1, 2009, pp. 81-93.

[11] M. Brunato and R. Battiti, "Statistical learning theory for location fingerprinting in wireless LANs," Computer Networks, vol. 47, 2005, pp. 825-845.

[12] Z.L. Wu, C.H. Li, K.Y.N. Joseph and L. Karl, "Location estimation via support vector regression," IEEE Transactions on Mobile Computing, vol. 6, no. 3, 2007, pp. 311-321.

[13] P. Harley, "Short distance attenuation measurements at 900 MHz and 1.8 GHz using low antenna heights for microcells," IEEE Journal on Selected Areas in Communications, vol. 7, no. 1, 1989, pp. 5–11.

[14] R.L. Haupt and S.E. Haupt, Practical Genetic Algorithm, 2nd ed., Wiley-Interscience, 2004.